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Abstract:

Small scale axial air driven turbine (less than 10kW) is the crucial component in distributed power generation cycles and in compressed air energy storage systems driven by renewable energies. Efficient small axial turbine design requires precise loss estimation and geometry optimization of turbine blade profile for maximum performance. Loss predictions are vital for improving turbine efficiency. Published loss prediction correlations were developed based on large scale turbines; therefore, this work aims to develop a new approach for losses prediction in a small scale axial air turbine using computational fluid dynamics (CFD) simulations. For loss minimization, aerodynamics of turbine blade shape was optimized based on fully automated CFD simulation coupled with Multi-objective Genetic Algorithm (MOGA) technique. Compare to other conventional loss models, results showed that the Kacker & Okapuu model predicted the closest values to the CFD simulation results thus it can be used in the preliminary design phase of small axial turbine which can be further optimised through CFD modelling. The combined CFD with MOGA optimization for minimum loss showed that the turbine efficiency can be increased by 12.48% compare to the baseline design.

Keywords: Small Scale Axial turbine, CFD, Total Loss, Optimization, Genetic algorithm.

Nomenclature:

Y_{total}	Total Loss Coefficient	[-]	s	Blade Spacing	[mm]
Y_{Tl}	Trailing Loss coefficient	[-]	$\Delta\eta$	Efficiency change	[-]
Y_P	Profile Loss Coefficient	[-]	η_o	Efficiency at zero clearance	[-]
Y_s	Secondary Loss Coefficient	[-]	η_{tt}	Total to total efficiency	[-]
Y_k	Tip Clearance Loss	[-]	α_{in}	Inlet flow angle	[Degree]
Y_{shock}	Loss due to shocks	[-]	α_{out}	Exit flow angle	[Degree]
Y_N	Nozzle Pressure Loss Coefficient	[-]	α_m	mean angle	[Degree]
Y_R	Rotor Pressure Loss Coefficient	[-]	ε	Blade Deflection Angle	[Degree]
X_{Te}	Trailing Edge Correction factor	[-]	R_e	Reynolds number	[-]
x_i	Incidence factor	[-]	M_{in}	Inlet Mach number	[-]
X_{Re}	Loss correction factor	[-]	X_{AR}	Aspect ratio coefficient	[-]
ΔE_{Te}	Energy loss coefficient at TE	[-]	k'	Effective tip clearance	[mm]
K_P	Mach number Factor	[-]	M_{out}	Exit Mach number	[-]
ζ^*	Nominal loss factor	[-]	h_{o1}	Total Inlet Enthalpy	[J/kg.K]
ζ_N	Nozzle Loss Coefficient	[-]	h_{o3}	Total Exit Enthalpy	[J/kg.K]
ζ_R	Rotor Loss Coefficient	[-]	h_3	Static Exit Enthalpy	[J/kg.K]
L	Lift Force	[N]	C_2	Nozzle Exit Absolute Velocity	[m/sec]
D	Drag Force	[N]	W_3	Rotor Exit Relative Velocity	[m/sec]
C_L	Lift Coefficient	[-]	S	Entropy	[J/kg.K]
C_D	Drag Coefficient	[-]	T_3	Exit Static Temperature	[K]
τ	Tip clearance	[mm]	P_o	Total Pressure	[Pa]
H	Blade height	[mm]	P	Static Pressure	[Pa]
c	Blade chord	[mm]	OF	Objective Function	[-]
V_∞	Main stream velocity	[m/sec]	r_H	Hub radius	[mm]
P_{in}	Inlet pressure	[Pa]	r_T	Tip radius	[mm]
P_{out}	Outlet pressure	[Pa]			

1. Introduction:

The availability of efficient small scale axial air turbines (less than 10kW) is vital for the development of renewable energy systems like the solar thermal air driven Brayton cycle [1, 2] and small scale compressed air energy storage systems [3, 4],where compressed air can be used to drive air turbines and generate power output.

The preliminary design phase of axial turbines starts with one dimensional mean line calculations which assume that the flow can be represented at turbine blade mid-span. Detailed description about mean line design approach is provided by many text-books e.g. [5-7] and some parameters selections are left to the designer for optimum blade configuration. In conventional turbine design, the one dimensional mean line approach is followed by through flow analysis or 2D inviscid design calculations to consider the variations in flow along turbine blade span. The through flow analysis can be conducted in the case of large scale turbines with long blades with hub to tip ratio around 0.4 where the variations in flow are significant [8, 9].

Axial turbine performance prediction based on loss estmation using Ainely- Mthieson [10] correlations is the most widely used method in turbine design [11, 12]. This approach was improved by Dunham and Came [11], also Craig and Cox [12] proposed an improved correlations for losses prediction. Ainely- Mthieson correlations are based on many simplified assumptions and some tests of blade loss prediction for typical conventional gas turbine blades of 50’s with large blade sections [13] According to Craig & Cox [13] the use of traditional performance estimation methods (e.g. Ainely, Traaupel, Smith Chart, and Soderberg) in steam turbine design leads to unsuccessful results and improvements for loss predictions is required. Moustapha et al. [14] carried out a review of existing correlations for losses prediction and concluded Ainely- Mthieson correlations are less tolerant for recent turbine designs.

In general, the published losses predictions correlations have been developed for large scale turbines, but as turbine sizes get smaller the effect of aerodynamic losses becomes more significant, therefore, the development of more accurate loss prediction models is required for small scale turbines [15, 16].

Limited studies have been conducted to develop means for loss prediction in small scale axial turbines [17-19]. Therefore this work aims to develop a new approach to predict the losses in a small scale axial air turbine using computational fluid dynamics (CFD) simulations.

2. Axial Turbine Losses:

Efficient axial turbine design requires understanding of the aerodynamic losses generated due to the complex 3-D viscous flow through the turbine. These losses are classified as shown in Figure 1 into:

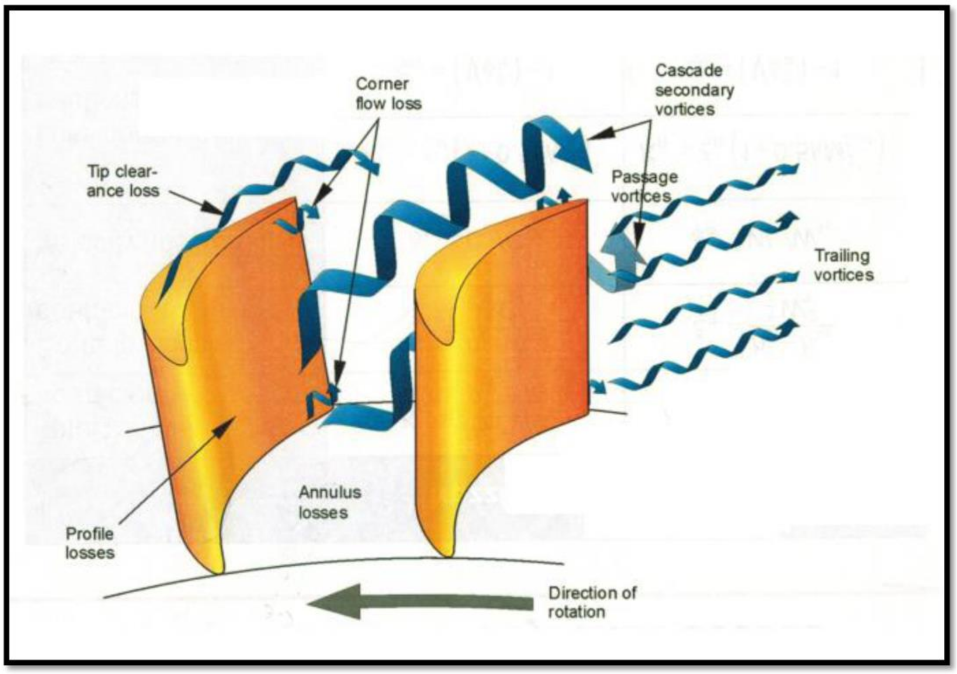

Figure 1: Loss Sources in Axial Turbine [6]

- **Profile Loss:** This loss is generated by the boundary layer formation due to the viscosity effect. The growth of this boundary layer is related to blade shape which causes boundary layer separation in some cases.

- **Annulus Loss:** This loss represents the skin friction loss at the end walls of turbine blade rows.

- **Secondary Loss:** This loss occurs near to the end walls boundary layer where the flow is turned due to pressure gradient and flow vortices are generated as a result of mixing secondary flow and main flow.

- **Tip Clearance Loss:** This loss occurs in the region between moving blades and casing leading to flow leakage. In tip clearance regions the leakage flow and main flow are mixed leading to vortex generation.

3. Axial Turbine Loss Coefficients:

To assess the losses occurring during expansion through the turbine, there are three loss coefficients which are related to the reduction in flow enthalpy compared with isentropic enthalpy [20]. These loss coefficients include:

- **Energy Loss Coefficient:** based on energy conservation law this coefficient defines the amount of energy that does not contribute to the generation of work [21].

$$\zeta_N = \frac{(h_3 - h_{3S})}{\frac{1}{2} C_{2s}^2} \tag{1}$$

$$\zeta_R = \frac{(h_3 - h_{3S})}{\frac{1}{2} W_{3s}^2} \tag{2}$$

This loss coefficient is another way of defining turbine efficiency which can be defined as:

$$\eta_{tt} = \frac{h_{o1} - h_{o3}}{h_{o1} - h_{o3ss}} \tag{3}$$

- **Entropy Loss Coefficient:** It is another way to define isentropic efficiency and it is expressed in terms of entropy change instead of enthalpy change based on second law of thermodynamics [21].

$$\zeta_N = \frac{(S_2 - S_1).T_3}{\frac{1}{2} C_2^2} \tag{4}$$

$$\zeta_{\mathrm{R}} = \frac{(\mathrm{S}_3 - \mathrm{S}_2).\mathrm{T}_3}{\frac{1}{2}\mathrm{W}_3^2} \tag{5}$$

- **Pressure Loss Coefficient:** it is a measure of loss in total pressure through turbine blades [21].

$$\mathrm{Y}_{\mathrm{N}} = \frac{(\mathrm{P}_{\mathrm{o}1} - \mathrm{P}_{\mathrm{o}2})}{(\mathrm{P}_{\mathrm{o}2} - \mathrm{P}_2)} \tag{6}$$

$$\mathrm{Y}_{\mathrm{R}} = \frac{(\mathrm{P}_{\mathrm{o}2\,\mathrm{rel}} - \mathrm{P}_{\mathrm{o}3\,\mathrm{rel}})}{(\mathrm{P}_{\mathrm{o}1\,\mathrm{rel}} - \mathrm{P}_3)} \tag{7}$$

According to Moustapha [14] the total loss coefficient (Y_{total}) can be converted into kinetic energy loss as:

$$Y_{total} = \frac{\left[1 - \frac{\gamma - 1}{2} M_{out}^2 \left(\frac{1}{\emptyset^2} - 1\right)\right]^{-\left(\frac{\gamma}{\gamma-1}\right)} - 1}{1 - \left(1 + \frac{\gamma - 1}{2} M_{out}^2\right)^{-\left(\frac{\gamma}{\gamma-1}\right)}} \tag{8}$$

Also, the total loss can be expressed in terms of blade aerodynamic characteristics as following [22]:

$$Y_{total} = \frac{C_D.\left(\frac{C}{S}\right).cos^2(\alpha_2)}{cos^3(\alpha_m)} \tag{9}$$

$$\mathrm{C}_{\mathrm{L}} = \frac{\mathrm{L}}{\frac{1}{2}\rho \mathrm{V}_\infty^2 \mathrm{C}} \tag{10}$$

$$\mathrm{C}_D = \frac{\mathrm{D}}{\frac{1}{2}\rho \mathrm{V}_\infty^2 \mathrm{C}} \tag{11}$$

4. Review of Existing Loss Prediction Correlations:

4.1. Soderberg Model:

Soderberg [8] developed a correlation to predict total profile and secondary losses but neglecting tip clearance:

$$\zeta_{\mathrm{N}} = \left(\frac{10^5}{\mathrm{Re}}\right)^{1/4} \left[(1+\zeta^*)\left(0.993 + 0.075\frac{\mathrm{l}}{\mathrm{H}}\right) - 1\right] \tag{12}$$

$$\zeta_{\mathrm{R}} = \left(\frac{10^5}{\mathrm{Re}}\right)^{1/4} \left[(1+\zeta^*)\left(0.975 + 0.075\frac{\mathrm{l}}{\mathrm{H}}\right) - 1\right] \tag{13}$$

Where ζ^* = the nominal loss factor given as:

$$\zeta^* = 0.04 + 0.06\left(\frac{\varepsilon}{100}\right)^2 \tag{14}$$

4.2. Ainely& Mathieson Model:

Using experimental data for conventional axial turbines Ainely and Mathieson [11] developed a method for losses prediction assuming that the effect of Mach number and flow outlet angles on pressure distribution can be neglected. The total losses are calculated by:

$$Y_{total} = (Y_P + Y_S + Y_{Tl})X_{Te} \tag{15}$$

Where χ_{Te} is the trailing edge correction factor, Y_P is profile loss, Y_S is secondary loss, and Y_{Tl} is trailing edge loss coefficient.

$$Y_{P(i=0)} = \left\{Y_{P(\alpha_{in}=0)} + \left(\frac{\alpha'_{in}}{\alpha_{out}}\right)^2 \left[Y_{P(\alpha_{in}=\alpha_{out})} - Y_{P(\alpha'_{in}=0)}\right]\right\}\left(\frac{t_{max}/l}{0.2}\right)^{\frac{\alpha_{in}}{\alpha_{out}}} \tag{16}$$

$$Y_s = \lambda \left(\frac{C_L}{t/_{l}}\right)^2 \left(\frac{cos^2\alpha_{out}}{cos^3\alpha_m}\right) \tag{17}$$

Where C_L is the lift coefficient and according to Xiao et al. [23] it can be calculated by:

$$C_L = 2\frac{t}{l}(tan\alpha_{in} - tan\alpha_{out})cos\alpha_m \tag{18}$$

4.3. Dunham & Came:

This model modifies the Ainely & Mathieson approach by considering the influence of Reynolds number on turbine losses [11].

$$Y_{total} = \left((Y_P + Y_S)\left(\frac{Re}{2\times 10^5}\right)^{-0.2} + Y_{Tl}\right)\chi_{Te} \tag{19}$$

$$Y_P = [1 + 60(M_{out} - 1)^2]\chi_i Y_{P(i=0)} \tag{20}$$

$$Y_s = 0.0334(\frac{l}{H})[4(tan\alpha_{in} - tan\alpha_{out})^2]\left(\frac{cos^2\alpha_{out}}{cos\alpha_m}\right)\left(\frac{cos\alpha_{out}}{cos\alpha_{in}}\right) \tag{21}$$

$$Y_{Tl} = B\frac{l}{h}\left(\frac{\tau}{l}\right)^{0.78} 4(tan\alpha_{in} - tan\alpha_{out})^2\left(\frac{cos^2\alpha_{out}}{cos\alpha_m}\right) \tag{22}$$

Where τ is the tip clearance, h is the annulus height, and B is a constant equals 0.47 for unshrouded blade and 0.37 for shrouded blade.

4.4. Kacker & Okapuu:

Kacker & Okapuu [20] developed their correlation by adding the influence of shock losses into the loss calculation and new models for profile and secondary losses are presented[24].

$$Y_{total} = \chi_{Re}Y_P + Y_s + Y_{TI} + Y_{Te} \tag{23}$$

χ_{Re} is correction factor and can be calculated using following equation:

$$\chi_{Re} = \left(\frac{R_e}{2\times 10^5}\right)^{-0.4} \quad for\ R_e \le 2\times 10^5 \tag{24}$$

$$\chi_{Re} = 1.0 \quad for\ 2\times 10^5 > R_e < 10^6 \tag{25}$$

$$\chi_{Re} = \left(\frac{R_e}{10^6}\right)^{-0.2} \quad for\ R_e > 10^6 \tag{26}$$

$$Y_P = 0.914\left(\frac{2}{3}K_P\chi_i Y_{P(i=0)} + Y_{shock}\right) \tag{27}$$

Where χ_i is the incidence factor, K_P is Mach number factor, and Y_{shock} is losses due to shocks.

$$K_P = 1 - 1.25(M_{out} - 0.2)\left(\frac{M_{in}}{M_{out}}\right)^2 \tag{28}$$

$$Y_{shock} = 0.75\left(M_{in,H} - 0.4\right)^{1.75}\left(\frac{r_H}{r_T}\right)\left(\frac{P_{in}}{P_{out}}\right)\frac{1-\left(1+\frac{\gamma-1}{2}M_{in}^2\right)^{\frac{\gamma}{\gamma-1}}}{1-\left(1+\frac{\gamma-1}{2}M_{out}^2\right)^{\frac{\gamma}{\gamma-1}}} \tag{29}$$

$$M_{in,H} = M_{in}\left(1 + K * ABS(\frac{r_H}{r_T} - 1)^{2.2}\right) \tag{30}$$

K =1.8 for stator and 5.2 for rotor.

$$Y_s = 0.04\left(\frac{l}{H}\right)\chi_{AR}[4(tan\alpha_{in} - tan\alpha_{out})^2]\left(\frac{cos^2\alpha_{out}}{cos\alpha_m}\right)\left(\frac{cos\alpha_{out}}{cos\alpha_{in}}\right)\left[1-\left(\frac{l_x}{H}\right)^2(1-K_P)\right] \tag{31}$$

The trailing edge loss coefficient can be calculated as:

$$Y_{Te} = \frac{\left[1+\frac{\gamma-1}{2}M_{out}^2\left(\frac{1}{1-\Delta E_{Te}} - 1\right)\right]^{-\gamma/_{\gamma-1}} - 1}{1-\left(1+\frac{\gamma-1}{2}M_{out}^2\right)^{-\gamma/_{\gamma-1}}} \tag{32}$$

For unshrouded blade the tip leakage is calculated by:

$$\Delta\eta = 0.93\left(\frac{r_T}{r_m}\right)\left(\frac{1}{Hcos\alpha_{out}}\right)\eta_o\Delta\tau \tag{33}$$

Where $\Delta\eta$ is the variation of efficiency with and without clearance, and η_o is the efficiency with zero clearance.

For the shrouded blades the leakage losses can be calculated using the following equation:

$$\mathrm{Y_k} = 0.37\frac{c}{h}\left(\frac{k'}{c}\right)^{0.78} 4(tan\alpha_{in} - tan\alpha_{out})^2\left(\frac{cos^2\alpha_{out}}{cos^3\alpha_m}\right) \tag{34}$$

Where k' = the effective tip clearance.

5. CFD Modelling and Losses Prediction:

Due to the cost of performing experimental tests and as a result of rapid increase in computing power, CFD has become an alternative powerful tool for understanding flow characteristics in turbo-machines [25, 26]. CFD can provide all the flow features, pressure distribution, and aerodynamic characteristics for turbine blades which enable the loss coefficients to be determined and compared to those calculated using equations 8-10. In this study, full CFD analysis for micro scale axial turbine was carried out using ANSYS CFX 15 which is based on finite volume technique to solve flow governing equations. Shear Stress Transport (SST) k-ω turbulent model was chosen for the simulation due its capability of near-wall treatment [27].

From one dimensional mean line code the turbine stage geometry for both nozzle and rotor were defined and constructed through ANSYS Blade-Gen. Using CFX Turbo-Grid the domain mesh was generated as shown in Figure 2.

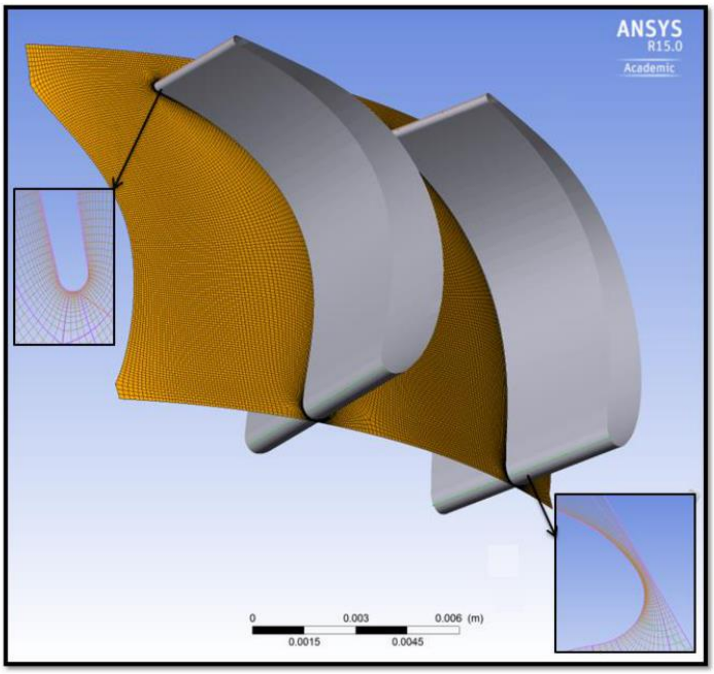

Figure 2: Mesh Generation (Fine 650,000 cells)

In order to validate the CFD analysis and as a result of unavailable experimental data for small scale axial turbine, the simulation was carried out for the large scale axial turbine geometry and the experimental data published by Wei [26] using the same geometrical parameters and boundary conditions. Figure 3 shows the predicted (CFD) efficiency compared to the experimental one with +/- 10% deviations.

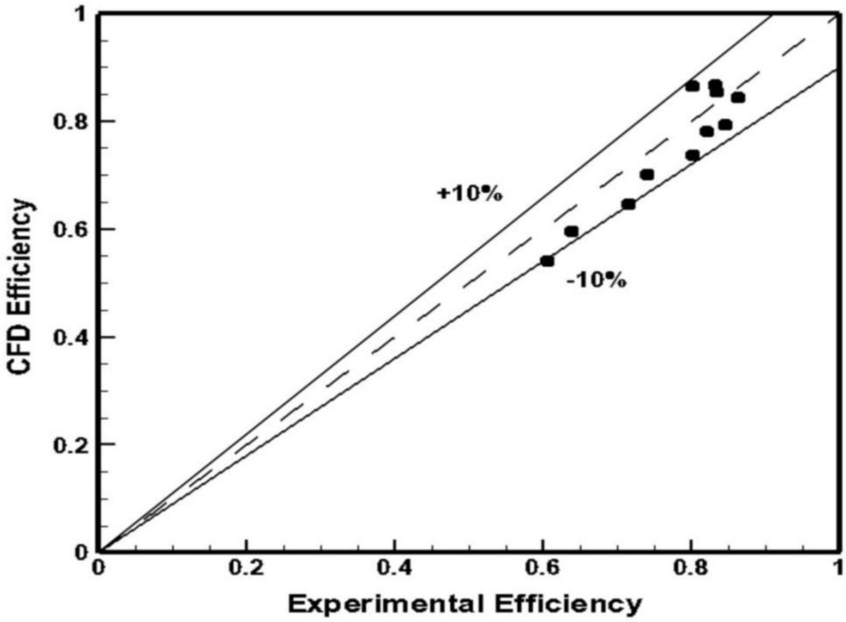

Figure 3: CFD Model Validation

6. Turbine Design Optimization for Minimum Loss:

Selecting the turbine blade profile which produces minimum losses is a multi-iterative and complex task which requires the application of advanced optimization techniques or expensive actual test of many blade profiles. The integration of the optimization algorithm with simulation software can be used as an effective tool for turbine design optimization. The advantage of this approach is that the design candidates can be generated using design of experiments method with a high flexibility in choosing design parameters levels and different optimization criteria can be applied [26, 28, 29].

To obtain optimum blade geometry, the optimization process requires a full definition of all blade geometrical parameters and constrains. Well known method of aerofoil cross section parameters definition is published by Pritchard [30] who described the blade profile by eleven parameters including flow angles, axial blade chord, turning angle, leading edge radius and trailing edge thickness as shown in Figure 4.

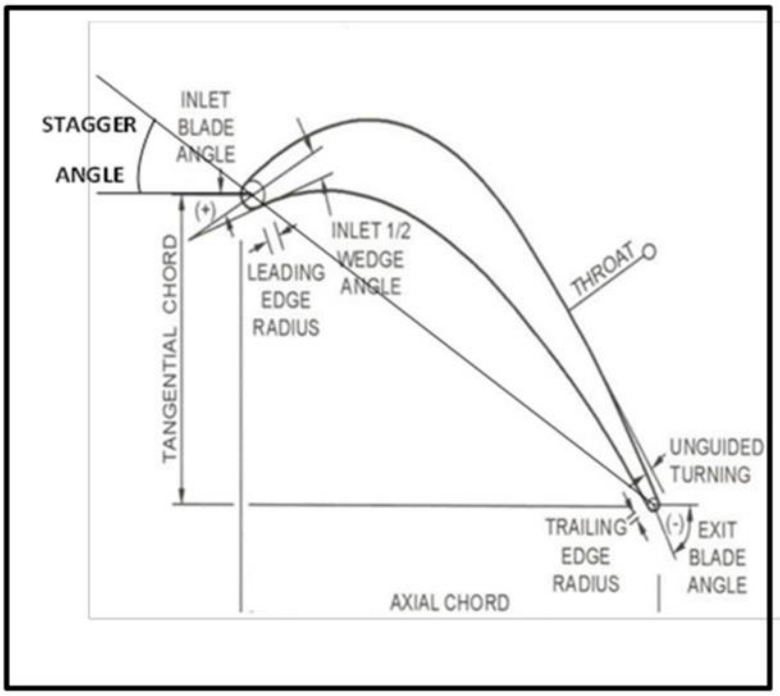

Figure 4: Blade Geometry Parameters [6]

A three-dimensional steady flow simulation using ANSYS CFX15 was created for blade profile optimization. ANSYS CFX design explorer can use design of experiments (DoE) which is used to generate sufficient data (design points) based on the number of input and output parameters including the interactions between design variables. The DoE approach can be applied for numerical modelling systems to predict the output response as a function of design parameters which can be optimized for maximum or minimum output response. The design explorer also applies response surface method (RSM) which is used in design optimization to build a relationship between independent design variables (input parameters) and the output response (output parameter) [31]. The general optimizations strategy using ANSYS CFX is described by a flowchart shown in Figure 5.

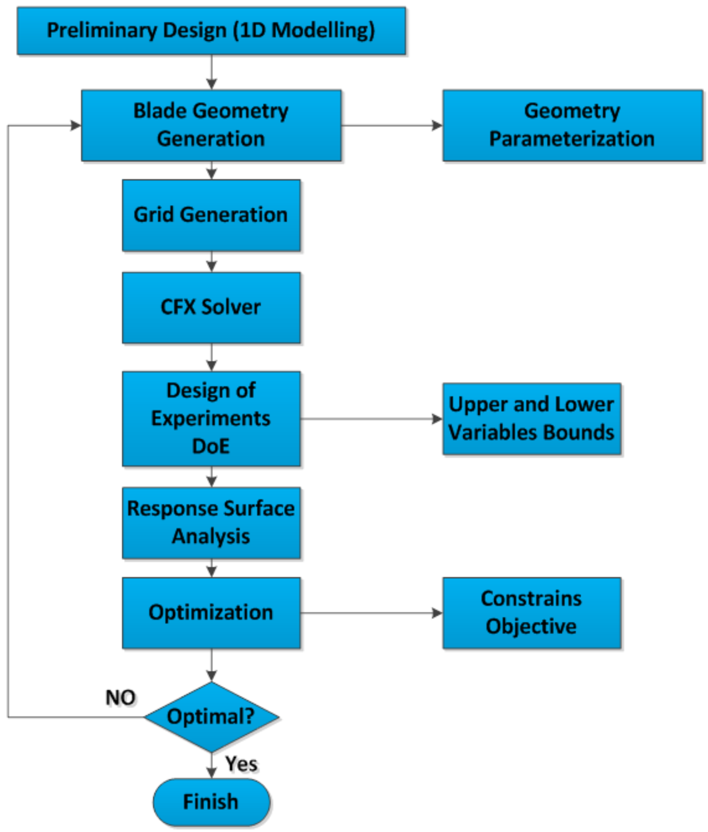

Figure 5: Optimization Strategy Description

7. Multi-objective Genetic Algorithm (MOGA):

In axial turbine development, the designer needs to optimize the blade profile for maximum efficiency. The turbine blade profile and flow path design can be optimized at the mean radius using genetic algorithms (GAs) to identify blade aerodynamic geometry for maximum performance [32]. However, the turbine design optimization for higher efficiency is multi-objective problem. Multi- objective genetic algorithm is an evolutionary algorithm with several objective functions which are optimised simultaneously and subjected to inequality and equality constrains [33]. According to Coello et al. mathematically MOGA can be formulated in a vector form as [34-36]:

The objective function vector: $F(X) = [f_1(X), f_2(X), \ldots \ldots f_k(X)]^n$

Subject to: $g_i(X) \leq 0 \quad i = \{1, \ldots .m\}$

$h_j(X) = 0 \quad j = \{1, \ldots .p\}$

Where k is the dimensional space of the objective functions $g_i(X)$ is the inequality constrains, and $h_j(X)$ is the equality constrains.

In this study, there are two objective functions considered in Multi-objective optimisation algorithm. The first objective function (to be maximized) is turbine total to total efficiency (η_{tt}), and the second objective function (to be minimised) is total pressure loss through turbine rotor (Y_R).

Maximize: $$OF_1 = \eta_{tt} = \frac{h_{o1} - h_{o3}}{h_{o1} - h_{o3ss}} \tag{35}$$

Minimize: $$OF_2 = \mathrm{Y_R} = \frac{(\mathrm{P_{o2\,rel}} - \mathrm{P_{o3\,rel}})}{(\mathrm{P_{o1\,rel}} - \mathrm{P_3})} \tag{36}$$

8. Results and Discussion:

8.1. CFD Loss Prediction:

This section presents a comparison between losses prediction using published correlations and losses obtained based on CFD simulation using ANSYS CFX for the operating conditions which are provided in Table1 and the total pressure loss was extracted from CFD and calculated using equation (7).

Table (1): Turbine Design Parameters:

Power output (kW)	5	Total inlet temperature (K)	360
Mass flow rate (kg/sec)	0.3225	Inlet relative flow angle ($degree$)	59.04
Shaft speed (rpm)	14000	Exit absolute flow angle ($degree$)	65.12
Total inlet Pressure (kpa)	200	Hub-tip ratio	0.75
Rotor Mean radius (mm)	35	Rotor span (mm)	10
Solidity	1.613	LE Wedge Angle($degree$)	22.5
Rotor Stagger Angle (degree)	19.5	Camber Angle (degree)	52.14

Figures 6 and 7 present the predicted rotor total loss coefficient for different rotational speeds (5,000-25,000) and a range of pressure ratios (1.5-3.5) which represents both on and off design conditions. The loss was predicted using Came & Dunham, Kacker & Okapuu, and Ainely colorations and compared with loss obtained by CFD simulation.

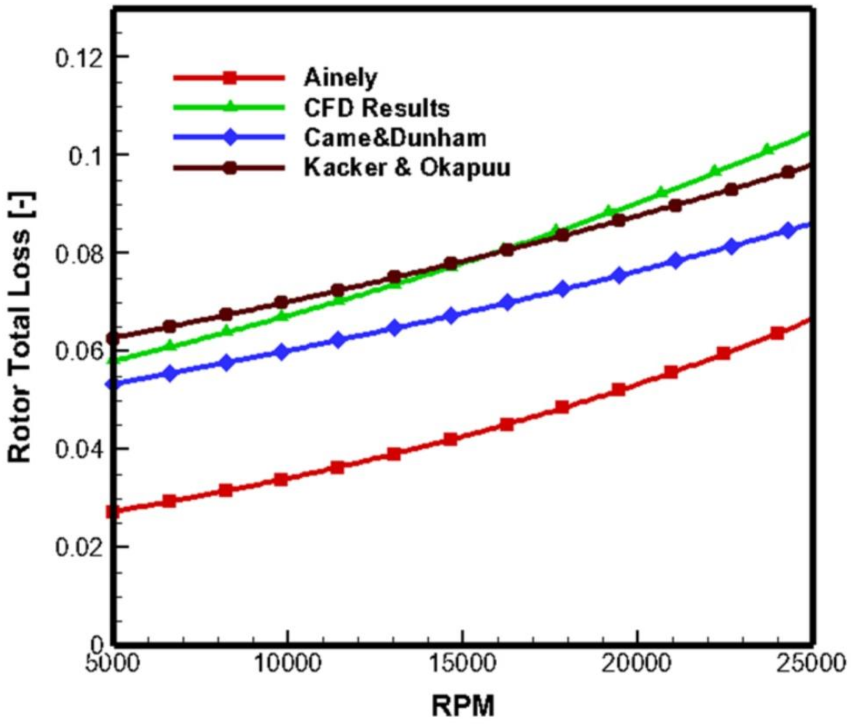

Figure 6: Rotor Total Loss Coefficient for different RPM

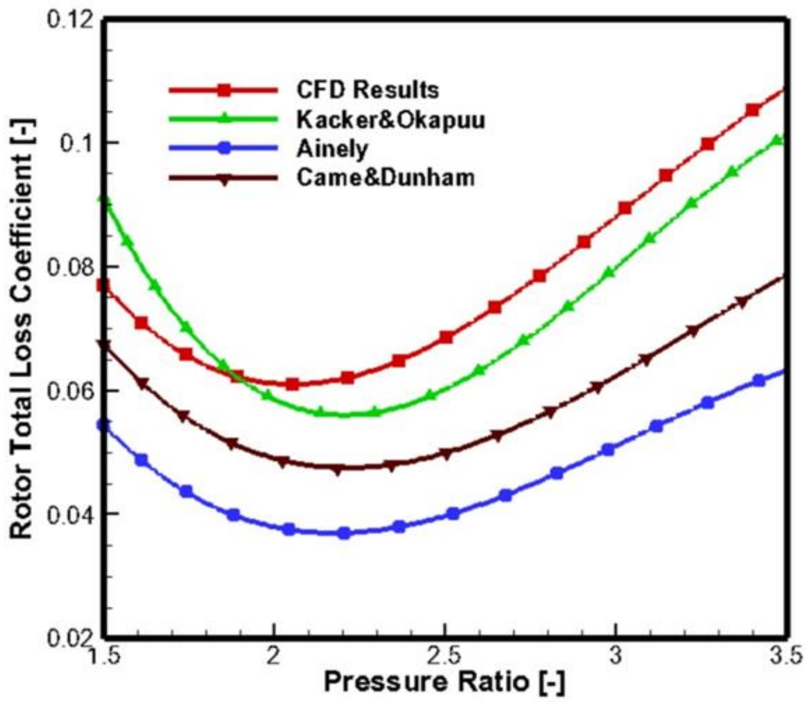

Figure 7: Rotor Total Loss Coefficient for different Pressure Ratio

It is clear from these figures that Kacker & Okapuu predicted losses are the closest to CFD results, while results by Ainely & Mathieson approach are the lowest loss values. Furthermore, Kacker & Okapuu Model was close to CFD near to design point (pr=2, RPM=14,000) and these results deviates for off design conditions. Therefore, the CFD was used to carry out a parametric analysis to study the effects of turbine blade geometry like trailing edge thickness as shown in Figure 8.

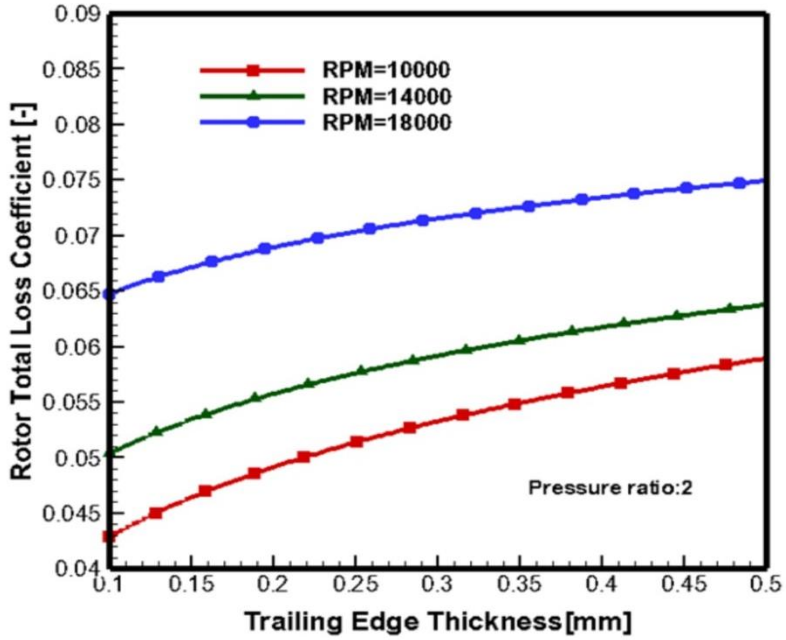

Figure 8: Rotor Total Loss Coefficient vs. Trailing Edge Thickness

The impact of blade incidence angle (i) (the difference between inlet flow angle and blade angle) on loss generation is presented in Figure 9. It can be seen that the rotor total losses increases gradually for both positive incidence (0 to +15^o) and negative incidence (0 to -15^o). As a result of the significant impact of blade incidence on loss generation, it is important to identify the influence of leading edge geometry on loss generation.

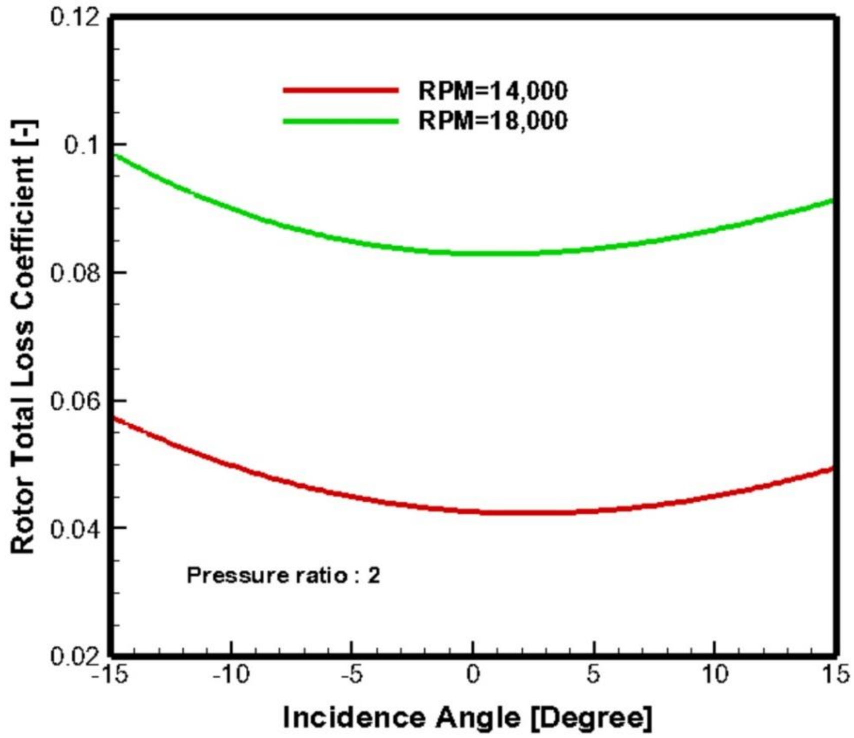

Figure 9: Rotor Total Loss Coefficient vs. Incidence Angle

8.2. Optimization Results:

From the results of loss prediction, it is obvious that the loss development is correlated with the blade profile geometry parameters. For efficient aerodynamic blade profile with minimum loss, the design optimization was performed through 3D CFD simulation and MOGA. The turbine blade geometric parameters were varied for different operating conditions to identify the optimum blade thickness distribution that satisfy the design goals with minimum total loss and higher performance.

Figure (10) shows the change in rotor total loss due to the variations in blade stagger angle. It shows that for a 5 kW compressed air axial turbine the best stagger angle is 21.48^{o}. The stagger angle is one of critical parameters due to its significantly impact on the thickness distribution, throat area, and turbine overall performance.

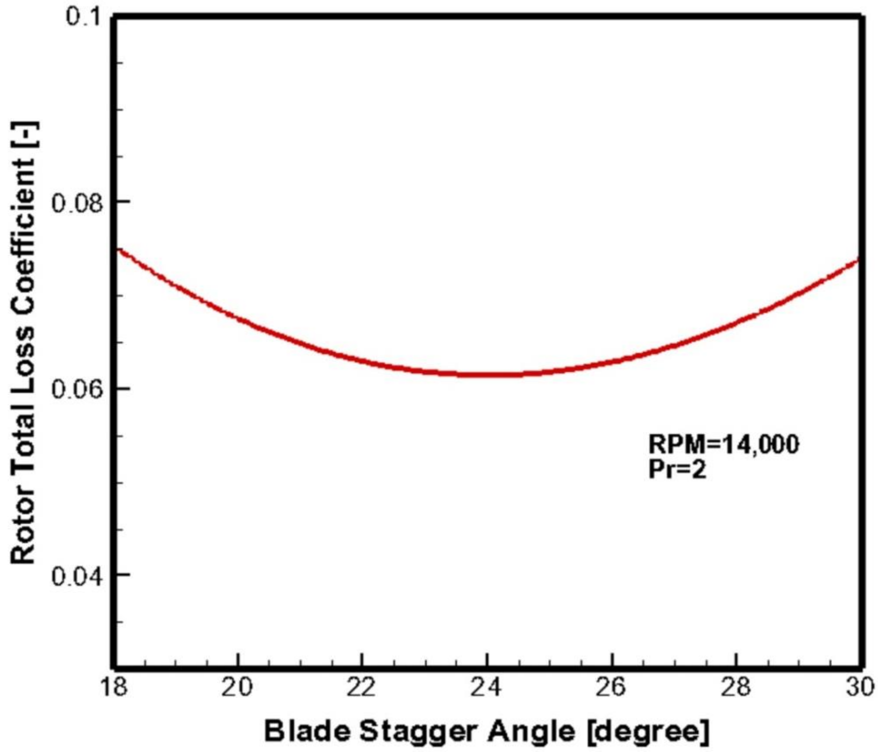

Figure 10: Rotor Total Loss Coefficient for different Stagger Angle

CFD modelling of the original blade baseline design and optimized blades (Figure 11) was carried out and results are provided in terms of entropy generation. The loss distribution on turbine blades can be evaluated by entropy generation as the key feature that measures aerodynamic loss through turbine passage.

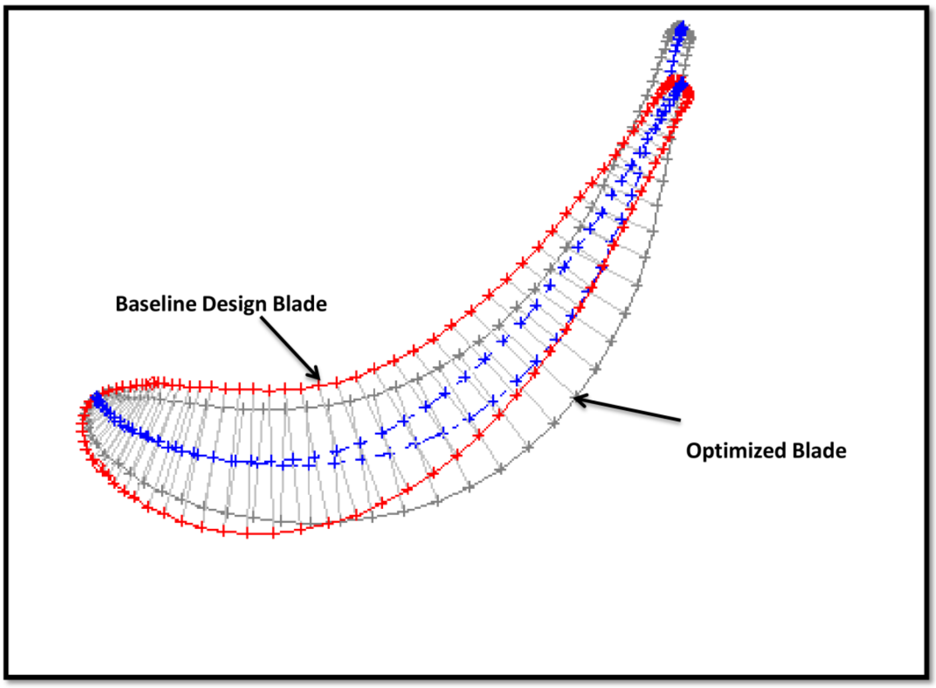

Figure 11: Original and Optimized Blade Profiles

Figure (12) shows the entropy generation contours of both baseline turbine design and optimized turbine. By comparing these two entropy contours, it can be observed clearly that the optimization approach could reduce maximum entropy generation rate from (216 J/kg.K) to (136 J/kg.K). This comparison between the baseline blade design and the optimised blade shows the dominant effect of blade thickness distribution on turbine aerodynamic performance and loss development. As can be seen, the optimization approach could reduce the flow loss through blade geometry variations (blade profile redesign) as a result of the dependence of boundary layer development, pressure, and flow velocity on blade surface curvature. The blade thickness distribution is characterized by blade stagger angle, leading and trailing edge geometries. Through the optimization, the flow separation at LE and TE can be avoided. Also the pressure distribution can be improved along the blade surface to overcome local flow acceleration and deceleration.

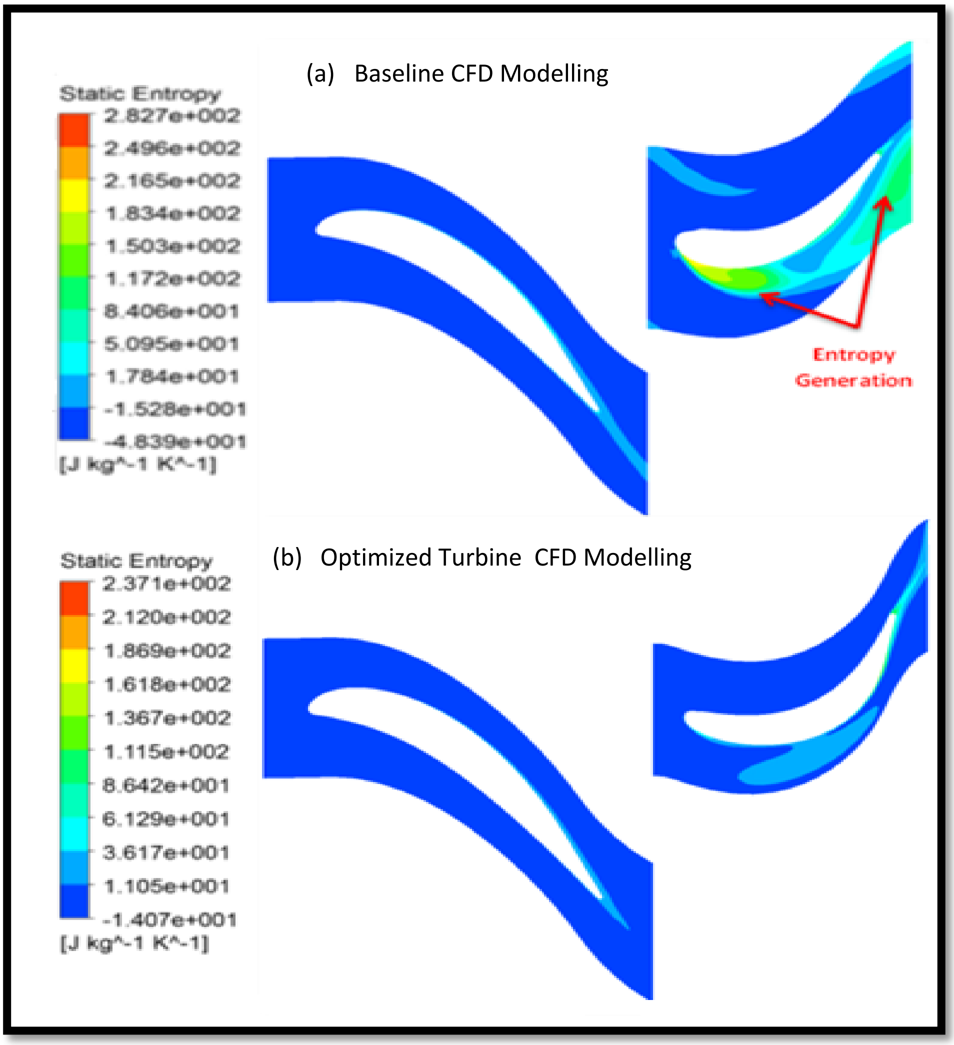

Figure 12: Entropy Generation contours: (a) Baseline Design (b) Optimized Design

Table (2) provides a detailed description of blade geometrical parameters and the performance of the turbine design produced through iterative parametric CFD analysis and optimised turbine for the 5kW compressed air axial turbine indicating a 12.34% increase in efficiency.

Table (2): CFD-MOGA Optimization Results:

Minimize P4;Pressure Loss	Goal, Minimize Mize P4 (Default importance); Strict Constraint	
Seek P5 = 5000 W	Goal, Seek P5 = (Default Importance)	
Optimization Method	The MOGA method (Multi-Objective Genetic Algorithm)	
Configuration	100 samples per iteration	
	Baseline Design	**Optimized Design**
Stager angle (m)	19.50	23.48
Number blades	22	18
Tip Clearance (m)	0.001268775	0.00098821
Leading. Major radius (m)	0.000227	0.000386
Leading. Minor radius (m)	0.0001274	0.0001133
Trailing. Major radius (m)	0.0005	0.00033
Trailing. Minor radius (m)	0.0003	0.00013
Wedge Angle (degree)	21.5	18.07
Stator-Rotor Gap (mm)	5.0	4.15
Throat (m)	0.004077	0.0032628
Rotor Pressure Loss Coeff.	0.087512	0.060234
Effs out (Total-to-Total)	76.8479	87.7861
Output Power (W)	4977.407	4463.227

9. Conclusion:

For efficient small scale air driven axial turbines, the loss predictions are crucial for design and development. The published conventional loss prediction models are developed for large scale turbines. Therefore there is a need for an effective approach to predict and minimise such losses for the small scale axial turbines. This work compares the predicted losses based on published literature correlations with those from CFD simulations. Results showed that the Kacker & Okapuu model predicted the closest values to the CFD simulation results and hence can be used to predict losses for small axial turbines. Also, the combined 3D CFD with MOGA optimization technique can be used to minimise total loss coefficient and produce the optimum design parameters in terms of blade stagger angle, stator to rotor spacing and number of blades, etc. This combined approach can be used to achieve higher total to total efficiency with up to 12.48% increase highlighting the potential of this developed technique.

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